Firm Level Productivity, Risk, and Return*

Ayşe İmrohoroğlu† Şelale Tüzel‡

October 2010

Abstract

This paper documents a strong link between firm level total factor productivity (TFP) and several firm characteristics such as size, book to market ratio, investment, and hiring rate. TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future excess returns and ex-ante discount rates. Low productivity firms on average earn 7% annual premium over high productivity firms in the following year and the premium is countercyclical. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. A production-based asset pricing model with aggregate and idiosyncratic shocks is shown to be able to account for most of these stylized facts quantitatively.

*We have benefited from conversations with Wayne Ferson, Selo Imrohoroglu, Ravi Jagannathan, Doug Joines, and seminar participants at USC, University of Hawaii, Ozyegin, Koç University, Early Career Women in Finance Conference, and the Federal Reserve Bank of New York. We are especially grateful to Chris Jones, Oguzhan Ozbas, Monika Piazzesi, and Vincenzo Quadrini for many insightful discussions. We thank Kewei Hou for sharing their implied cost of capital data.

†Department of Finance and Business Economics, Marshall School of Business, University of Southern California, Los Angeles, CA 90089-1427. E-mail: ayse@marshall.usc.edu

‡Department of Finance and Business Economics, Marshall School of Business, University of Southern California, Los Angeles, CA 90089-1427. E-mail: tuzel@marshall.usc.edu.

1 Introduction

Empirical research in finance has documented significant differences in financial returns across firms. These differences have been linked to observable characteristics of firms, such as size and ratio of a firm's book value to market value as in Fama and French (1992); investment growth as in Titman, Wei, and Xie (2003); investment to assets as in Lyandres, Sun, and Zhang (2008); asset growth as in Cooper, Gulen, and Schill (2008); investment to capital ratio and the hiring rate as in Bazdresch, Belo, and Lin (2010); inventory investment rate as in Wu, Zhang, and Zhang (2010) and Belo and Lin (2010); and real estate ratios of firms as in Tuzel (2010).[1]

Recently, a growing strand of literature has tied such differences in firm characteristics and returns to optimal investment decisions of firms in response to changes in productivity and discount rates.[2] However, none of these papers has directly estimated firm level productivity. In this paper, we estimate firm level productivity using the semi-parametric method initiated by Olley and Pakes (1996) and construct a panel of TFP levels for each firm/year observation for the cross-section of publicly traded manufacturing firms in the U.S.[3] Using this data we examine the link between firm characteristics, excess returns, and firm level total factor productivity (TFP).

We establish a set of stylized facts by examining the summary statistics of firms sorted into ten equally weighted TFP portfolios between 1973 and 2005. Our findings indicate that high TFP firms are typically growth firms with an average book to market ratio of about 0.5 and low TFP firms are value firms with an average book to market ratio of about 1.5. We find the relationship between firm size and TFP to be monotonically increasing. The average size of the firms in the lowest TFP decile is 17% of the average size of all firms in that year, whereas the size of firms in the highest TFP decile is 289% of the average size. In addition, the hiring rate, fixed investment to capital ratio, asset growth, profitability, and inventory growth are all monotonically increasing in firm level TFP. These results are consistent with the view that firm level productivity is a state variable that effects firms' investment and hiring decisions and leads to different firm characteristics.

We merge our TFP data with monthly stock returns from the Center for Research in Security Prices. We find that TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future excess returns and ex-ante discount rates. Low productivity firms on average earn 5% annual premium over high

[1] A partial list of papers documenting firm characteristics related to average stock returns include Ball (1978); Banz (1981); Basu (1983); DeBondt and Thaler (1985); Bhandari (1988); Jegadeesh and Titman (1993); Chan, Jegadeesh, and Lakonishok (1996); Sloan (1996); and Thomas and Zhang (2002).

[2] Some of the papers in this literature include Gomes, Kogan, and Zhang (2003); Zhang (2005); Gourio (2007); Bazdresch, Belo, and Lin (2010); Li, Livdan, and Zhang (2009); and Belo and Lin (2010), among others.

[3] Since firm level productivity is the major ingredient of our empirical work, its estimation is critical. An important advantage of the Olley and Pakes (1996) approach is its ability to control for selection and simultaneity biases. In our sensitivity analysis, we expand the basic production function in Olley and Pakes (1996) to include several different specifications.

productivity firms in the following year. However, there is significant variation in the premium over the business cycles; the return spread is about three times as high during NBER contractions as it is during expansions. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. Examination of Fama-MacBeth cross sectional regressions of monthly stock returns on lagged firm level TFP as well as other control variables shows that the cross sectional regressions produce negative and statistically significant average slopes for TFP. Overall, we find about 3.5% higher expected returns for the firms in lowest TFP decile compared to a firm with average TFP.

We confirm the negative relationship between firm productivity and expected returns using an ex ante measure of discount rates, the implied cost of capital of Hou, van Dijk, and Zhang (2010). We find that the average implied cost of capital for the low TFP portfolio exceeds that of the high TFP portfolio by approximately 4%, and the spread is highly significant. Similar to average future returns, the spread in implied cost of capital is also countercyclical.

A number of results emerge from our firm level productivity estimation. We estimate the persistence of firm level TFP as 0.91 and the standard deviation of the TFP shock as 0.12 at the quarterly frequency. These estimates provide empirical support for the productivity parameters used, for example, by Zhang (2005), Gomez (2001), and Hennessy and Whited (2005) where the parameters are calibrated so that the models used can match moments of some of the key variables.[4] We also document an increase in the cross sectional dispersion of firm level productivity from 0.20 in 1960s to almost 0.50 in 2005. This fact might be important in understanding the increase in the idiosyncratic volatility of stock returns documented by Campbell, Lettau, Malkiel and Xu (2001).

We propose a production-based asset pricing model to examine the link between productivity and expected returns similar to the models used in Zhang (2005) and Bazdresch, Belo, and Lin (2010). In this framework, firms are ex-ante identical but diverge over time due to idiosyncratic shocks. They also face aggregate shocks and incur adjustment costs upon changes in the capital stock. We pair this model of production with an exogenous pricing kernel that generates countercyclical price of risk. Firms that receive high productivity shocks have high investment and hiring rate, low B/M ratio and end up being large firms. In the presence of frictions in adjusting capital, the negative relationship between a firm's productivity and its level of risk arises endogenously. In recessions (low aggregate productivity), most firms try to scale back their production and lower their investments and hiring. Even though all firms suffer from low aggregate productivity, the firms that suffer the most are the ones with low firm level TFP. These firms have the most pressure to scale back and hence suffer the most from adjustment costs that result in low firm values and low returns, especially in the presence of countercyclical price of risk. Since the returns of low productivity firms fluctuate more closely with aggregate productivity in recessions, they are particularly riskier in recessions. The opposite happens in expansions.

[4] In addition, Gourio (2008) estimates the persistence of the idiosyncratic shock to be 0.7 annually using Compustat data on investment and profitability.

We calibrate the model to match time series properties of aggregate stock returns and examine the cross section of firm characteristics and stock returns that are generated by the model economy. Our simulation results indicate that the model accounts for many of the cross sectional stylized facts documented in our empirical section. In particular, the dispersion in investment to capital ratio, hiring rate, book to market, size, and returns of low versus high TFP firms and its variation over the business cycle generated by the model captures the qualitative and some of the quantitative features of the data well.

Section 2 summarizes the data and our empirical results. Section 3 presents the model and the numerical results for the calibrated economy. Section 4 concludes. The Appendix provides detailed information on the estimation of firm level productivities and sensitivity results.

2 Empirical Results

We start this section by examining the relationship between firm level TFP and certain firm characteristics that have been linked to stock returns by previous research in finance. We investigate the extent to which productivity, an economic fundamental, is linked to the cross sectional dispersion in firm characteristics and stock returns. First, we examine the relationship between firm level TFP and certain firm characteristics by constructing portfolios sorted on firm level TFP. Next, we run Fama-MacBeth cross sectional regression of firm returns on firm level TFP and other control variables.

2.1 Data

The key variables for estimating the firm level productivity for the benchmark case are the firm level value added, employment, and physical capital. We obtained firm level data from Compustat and supplemented it with industry level data from the NBER-CES Manufacturing Industry Database.[5] The sample is an unbalanced panel with approximately 5700 distinct firms spanning the years between 1958 and 2005. Some of the key variables are firm level capital stock (k_{it}) given by gross Plant, Property & Equipment (PPEGT) and the stock of labor (l_{it}) given by the number of employees (EMP), both from Compustat. Fixed investment to capital ratio is given by firm level capital investment (Capital expenditures in Compustat) divided by the beginning of the period capital stock. Hiring rate at time t is the change in the stock of labor from time $t-1$ to t. Firm level value

[5] An alternative is to use the Longitudinal Research Database (LRD), which is a large panel data set of U.S. manufacturing plants developed by the U.S. Bureau of the Census. One major shortcoming of the LRD for our purposes is that it excludes data on headquarters, sales offices, R&D labs, and the other auxiliary units that service manufacturing establishments of the same company. Since our focus is on examining the link between firm level TFP and stock returns, missing a potentially important part of the firm activities is not desirable. Consequently, we use the Compustat data for measuring firm level TFP.

added is computed using Compustat data on sales, operating income and employees. We employ the semiparametric estimation procedure suggested by Olley and Pakes (1996) to obtain the firm level TFPs. In our TFP estimation, we use industry specific time dummies and take out the industry/year effect from firm TFPs. Hence our firm TFPs are free of the affect of industry or aggregate TFP in any given year. Detailed information about the data, its computation, the measurement of TFP, and its properties are provided in the Appendix.

Monthly stock returns are from the Center for Research in Security Prices (CRSP). We measure the contemporaneous returns over the same horizon as TFPs, matching year t TFPs to returns from January of year t to December of year t. In predictability regressions (calculating the future returns), to ensure that accounting information is already impounded into stock prices, we match CRSP stock return data from July of year t to June of year $t+1$ with accounting information for fiscal year ending in year $t-1$, as in Fama and French (1992, 1993), allowing for a minimum of a six month gap between fiscal year-end and return tests. In other words, we match the productivities calculated using accounting data for fiscal year ending in year $t-1$ to stock returns from July of year t to June of year $t+1$. Similar to Fama and French (1993), in order to avoid the survival bias in the data, we include firms to our sample after they have appeared on Compustat for two years. Also following Fama and French (1993), we only include firms with ordinary common equity as classified by CRSP in our sample, excluding ADRs, REITs, and units of beneficial interest. In order to ensure that we have at least 1000 firms in our sample every year, we start our sample period in 1972 for Compustat Data (1972-2005) and match them to stock return data from CRSP (July 1973 - June 2007).

2.2 Productivity and Firm Characteristics

Table 1 presents summary statistics for firms sorted into 10 equally weighted portfolios based on TFP in year t. The first row provides data on TFP levels of the firms in these portfolios where average TFP is normalized to be one. There is significant dispersion in firm level TFPs. Average TFP of the firms in the lowest TFP portfolio is slightly larger than half of the average TFP of all firms in that year, while it is 1.77 times the average TFP in the highest TFP portfolio.

In order to gauge the sensibility of our TFP measure, we contrast some of its properties with those obtained from longitudinal micro-level data sets such as the Longitudinal Research Database (LRD), which is a large panel data set of U.S. manufacturing plants developed by the U.S. Bureau of the Census. For example, using data for 4-digit textile industries, Dwyer (1997) finds the ratio of average TFP for plants in the ninth decile of the productivity distribution relative to the average in the second decile to be between about 2 and 4. Olley and Pakes (1996) find similar ratios in the telecommunications equipment industry. Using plant-level data from the 1977 Census of Manufactures, Syverson (2004) reports similar findings in four-digit manufacturing industries. The ratio of average TFPs between the high and low TFP portfolios obtained from our data set in Table 1 is 3.22. The ratio of the average TFP in the ninth decile to the average in the second decile is

1.7.

Results in Table 1 indicate that the hiring rate (growth in the number of employees), fixed investment to capital ratio, asset growth, investment to capital for organizational capital, and inventory growth are all monotonically increasing in firm level TFP. The differences in these firm characteristics between the high and low TFP portfolios are highly statistically significant for all cases. There is significant dispersion in investment to capital ratios of firms; the ratio for fixed investment ranges from 9% for low productivity firms to 32% for high productivity firms, whereas the ratio for organizational capital ranges between 36% to 120%.[6] The results are similar for hiring rate, inventory growth and asset growth. The firms in the lowest productivity decile reduce their workforce by around 6% and their assets shrink on average 2%, whereas firms in the highest productivity decile increase their workforce by 16% and experience more than 30% asset growth. Inventory growth varies between 6% and 30%. TFP is also related to research and development expense (R&D). The ratio of R&D expense to the plant property & equipment (PPE) of the firm also tends to increase with TFP, but the relationship is not perfectly monotonic.[7]

Market capitalization of firms monotonically increase with TFP. The average size of the firms in the lowest TFP decile is 17% of the average size of all firms in that year, whereas the average size of firms in the highest TFP decile is 289% of the average size.[8] The B/M ratios of the firms monotonically decline with increasing TFP indicating that high TFP firms are typically growth firms and low TFP firms are value firms. This finding is consistent with the mechanisms in rational explanations of the value premium, such as Zhang (2005) and Gala (2006). Table 1 also shows that the real estate ratio of low productivity firms exceed the average in their industry whereas the real estate ratio of high productivity firms is lower than their industry average, consistent with the mechanism in Tuzel (2010). The relationship between the average age (computed as the number of years since the firm first shows up in Compustat) and TFP is inverse U-shaped.

We look at additional firm characteristics that are found to be related to future stock returns. Net stock issues (net shares) are on average negative for all portfolios but are particularly low for high TFP firms. Profitability is monotonically and positively related to TFP, confirming that high productivity firms are also the most profitable.[9] Also, TFP is negatively related to leverage, with the least productive firms possessing the highest

[6] We measure organizational capital based on data on firm's reported sales, general, and administrative expenses. More details are provided in the Appendix.

[7] The data item for R&D expense is not populated for all firms. R&D expense can also be considered as a type of investment; however, taking R&D as a seperate capital item would lead to the exclusion of a significant part of our sample. In untabulated results, we find that constructing a capital stock from R&D expense using the perpetual inventory method and adding that capital stock to the fixed capital leads to similar results.

[8] Since the nominal sizes of the firms have a growing trend, we prefer to look at the relative sizes of the firms (firm size/average firm size in that year).

[9] We define profitability as equity income divided by book equity, following Fama and French (2008). We also looked into an alternative definition of profitability from Novy-Marx (2010), defined as gross profits divided by total book assets, which produced qualitatively very similar results (monotonically and positively related to TFP).

leverage.

Summary Statistics: 10 Portfolios Sorted on TFP

	Low	2	3	4	5	6	7	8	9	High	High-Low
TFP	0.55	0.73	0.81	0.87	0.92	0.97	1.03	1.11	1.24	1.77	1.22
Size	0.17	0.28	0.48	0.67	0.75	0.98	1.18	1.61	2.29	2.89	2.72
											(18.11)
B/M	1.47	1.39	1.21	1.08	0.99	0.91	0.82	0.73	0.64	0.52	-0.95
											(-11.40)
Fixed Inv/Capital	0.09	0.09	0.09	0.10	0.11	0.12	0.14	0.17	0.21	0.32	0.23
											(21.01)
Asset Growth	-0.02	0.05	0.07	0.11	0.12	0.14	0.18	0.19	0.24	0.32	0.34
											(20.16)
Hiring Rate	-0.06	0.01	0.02	0.04	0.05	0.08	0.08	0.11	0.12	0.16	0.22
											(18.72)
Inventory Growth	0.06	0.07	0.09	0.13	0.13	0.17	0.17	0.22	0.24	0.30	0.24
											(5.49)
OC Inv/OC	0.36	0.38	0.33	0.35	0.36	0.38	0.42	0.45	0.50	1.20	0.83
											(1.45)
R&D/PPE	0.13	0.07	0.06	0.07	0.08	0.09	0.09	0.11	0.17	0.26	0.13
											(9.83)
Real Estate Ratio	0.014	0.003	0.005	0.005	0.002	0.003	-0.003	0.001	-0.004	-0.010	-0.024
											(-4.30)
Net Share	-0.03	-0.02	-0.03	-0.02	-0.02	-0.03	-0.03	-0.04	-0.07	-0.11	-0.08
											(-6.21)
Leverage	0.27	0.30	0.28	0.26	0.24	0.22	0.19	0.17	0.14	0.10	-0.17
											(-12.63)
Profitability	-0.50	-0.09	0.03	0.18	0.07	0.09	0.13	0.26	0.16	0.23	0.72
											(10.29)
AGE	16.53	18.69	19.72	20.34	19.97	19.38	18.50	18.40	16.58	13.81	-2.72
											(-9.78)
Number of Firms	122	123	123	123	123	123	123	123	123	122	

Table 1: Descriptive Statistics for TFP Sorted Portfolios

2.3 Asset Pricing Implications

2.3.1 Returns of TFP-sorted portfolios

The relationships between firm characteristics and returns documented in prior research, when combined with the stylized facts presented in Table 1, imply a positive relationship between firm TFP and contemporaneous returns, while implying a negative relationship between TFP and future returns. In Table 2, we directly look at these relationships by presenting the contemporaneous and future annualized excess returns (excess of the risk free rate) of TFP sorted portfolios. The firms in each portfolio are equally weighted. Our results confirm that TFP is positively and monotonically related to contemporaneous stock returns. The difference between the returns of high and low TFP firms is 28.7%, and it is highly statistically significant. A positive productivity shock leads both to high TFP and high stock returns in that year. The relationship between TFP and future excess returns is equally striking: low productivity firms on average earn 4.9% annual premium over high productivity firms in the following year, and the return spread is statistically significant. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms.

In order to understand the relationship between TFP and future returns over the business cycles, we separate our sample to expansionary and contractionary periods as defined by the NBER (in June of each year) and look at the returns of TFP sorted portfolios over the following 12 months. We find that the negative relationship between TFP and expected returns persists both in expansions and in contractions. However, both the average level of expected returns (approximately 10% versus 34%), and the spread between the returns of high and low TFP portfolios (approximately 4% versus 13%) are much higher in contractions.

Excess Returns for TFP Sorted Portfolios (%, annualized)

	Low	2	3	4	5	6	7	8	9	High	High-Low
Contemporaneous Returns (Year *t*)											
Return	-3.95	3.80	8.76	10.92	11.60	14.75	16.37	16.27	20.52	24.75	28.70
t-stat	(-0.88)	(1.03)	(2.50)	(3.11)	(3.31)	(4.12)	(4.57)	(4.55)	(5.27)	(5.79)	(12.60)
Std	26.16	21.40	20.40	20.47	20.42	20.87	20.89	20.86	22.72	24.94	13.28
Future Returns (Year *t+1*)											
All states, 408 months	Low	2	3	4	5	6	7	8	9	High	High-Low
Return	15.21	16.86	13.31	13.66	12.87	12.72	12.33	11.10	10.70	10.30	-4.90
t-stat	(3.43)	(4.45)	(3.86)	(4.00)	(3.73)	(3.83)	(3.56)	(3.17)	(2.92)	(2.53)	(-2.22)
Std	25.88	22.09	20.08	19.90	20.11	19.39	20.20	20.39	21.32	23.77	12.87
Expansions, 360 months	Low	2	3	4	5	6	7	8	9	High	High-Low
Return	11.94	13.59	10.06	10.11	9.64	9.85	9.62	8.11	8.05	8.16	-3.78
t-stat	(2.59)	(3.46)	(2.83)	(2.92)	(2.73)	(2.89)	(2.75)	(2.27)	(2.15)	(1.97)	(-1.61)
Std	25.24	21.50	19.44	18.97	19.33	18.68	19.14	19.56	20.49	22.72	12.81
Contractions, 48 months	Low	2	3	4	5	6	7	8	9	High	High-Low
Return	39.72	41.36	37.65	40.27	37.13	34.24	32.63	33.51	30.52	26.36	-13.36
t-stat	(2.69)	(3.28)	(3.22)	(3.25)	(3.05)	(2.94)	(2.47)	(2.67)	(2.32)	(1.73)	(-2.02)
Std	29.58	25.22	23.41	24.74	24.36	23.33	26.38	25.12	26.35	30.40	13.22

Table 2: Excess Returns for TFP Sorted Portfolios

As we demonstrate in Table 1, TFP is significantly related to size and B/M at the firm level. Hence, we would like to investigate how returns of TFP sorted portfolios covary with SMB and HML and whether these factors can capture the variation in excess returns of TFP sorted portfolios.[10] Table 3 presents the alphas and betas of TFP sorted portfolios with respect to MKT, SBM, and HML factors (Fama and French, 1992, 1993, among others). Betas are estimated by regressing the portfolio excess returns on the factors. Alphas are estimated as intercepts from the regressions of excess portfolio returns. Monthly alphas are annualized by multiplying by 12. We find that low TFP portfolios load heavily on HML and SMB, whereas the loading of the high TFP portfolios are low, even negative in some cases. The three factors cannot capture all the variation in excess returns, and alphas decline with TFP. The portfolios that are long in high TFP portfolio and short in low TFP portfolio (High-Low) have an alpha around -1% though the spread in alpha is not statistically significant. Our takeaway from these results is not necessarily that TFP is a separate risk factor that is not captured by SMB and HML but rather that TFP is systematically related to SMB and HML, which we further investigate empirically and through a model economy.

Alphas and Betas of Portfolios Sorted on TFP

Dependent Variable: Excess Returns

	Low	2	3	4	5	6	7	8	9	High	**High-Low**
alpha	2.03	4.21	0.81	1.35	0.40	1.28	1.21	0.23	0.44	1.19	-0.84
	(0.97)	(2.60)	(0.61)	(1.08)	(0.35)	(1.11)	(1.13)	(0.20)	(0.38)	(0.89)	(-0.45)
MKT	1.04	0.99	1.03	1.06	1.07	1.04	1.06	1.06	1.09	1.15	0.11
	(24.81)	(30.52)	(38.89)	(42.22)	(46.49)	(44.80)	(49.48)	(45.59)	(46.73)	(42.65)	(3.02)
HML	0.34	0.44	0.51	0.48	0.48	0.38	0.28	0.24	0.11	-0.16	-0.50
	(5.41)	(9.03)	(12.72)	(12.88)	(13.83)	(11.12)	(8.66)	(6.96)	(3.04)	(-3.89)	(-8.85)
SMB	1.30	1.06	0.83	0.77	0.81	0.72	0.76	0.75	0.72	0.72	-0.58
	(23.99)	(25.21)	(24.18)	(23.91)	(27.10)	(23.94)	(27.62)	(24.88)	(23.91)	(20.48)	(-12.04)

Table 3: Fama-French Three Factor Model

Table 4 examines the returns of portfolios double sorted on TFP and B/M ratio as well as TFP and size. In June of each year t, we first sort the common stocks into three portfolios based on the firm's TFP in year t-1. Then, each of these three TFP portfolios are equally sorted into three portfolios based on their B/M (size) at the end of year t-1 (end of June in year t).[11] In the Panel A of Table 4, we report the equally weighted returns (July of year t to June of year t+1) for the TFP and B/M sorted portfolios. The

[10] MKT is excess market returns; SMB is returns of portfolio that is long in small, short in big firms; HML is returns of portfolio that is long in high B/M, short in low B/M firms.

[11] We do not perform independent sorts since there are few firms in off diagonal (low TFP & low B/M, high TFP and high B/M; low TFP & big, high TFP and small) portfolios.

results display large and statistically significant spreads in the average excess returns with respect to TFP for all B/M categories.

Panel B displays the average returns of portfolios double sorted on TFP and size. There is a significant spread in the returns of small and medium firms with respect to TFP. However, for the big firms, the spread is neither economically nor statistically significant. In other words, TFP does not seem to be relevant for the expected returns of biggest firms. This finding brings up the possibility that financing constraints the firms face may be relevant. In a recent paper, Hadlock and Pierce (2010) find that firm size is a particularly useful predictor of firms' financial constraints. The insensitivity of the biggest firms' expected returns to TFP may suggest that differences in TFP imply differences in risk and expected returns only when the firms are possibly financially constrained.[12] The only other variable Hadlock and Pierce (2010) find consistently useful in predicting financial constraints is firm age.[13] If the absence of financial constraints is the reason for the different behavior of biggest firms, we should find similar results when we control for firm age instead of firm size. We would expect not to find a significant relationship between the expected returns of the oldest firms and their TFP. Panel C of Table 4 reports the excess returns of portfolios sorted on firm age and TFP. We find that among the young and middle aged firms, those with low TFP earn a significant premium over those with high TFP. However, the return spread is smaller and less significant for older firms.

[12] Recently, Livdan, Sapriza, and Zhang (2009) study the effect of financial constraints on risk and expected returns by extending the standard investment-based asset pricing framework. In their model, financially constrained firms cannot finance all desired investments and hence are less flexible in dealing with aggregate and firm level productivity shocks. This mechanism makes low productivity firms especially risky.

[13] Hadlock and Pierce (2010) report that the only variables that consistently predict a firm's constraint status after controlling for size and age are a firm's leverage and cash flow. However, given the endogeneous nature of these variables, they recommend that researchers rely solely on firm size and age, two relatively exogenous firm characteristics, to identify constrained firms.

Excess Returns of Double Sorted Portfolios

Panel A: TFP and B/M				
TFP	Growth	Medium	Value	Growth-Value
Low	11.80	14.62	18.90	7.10
				(3.61)
Medium	8.19	12.77	16.51	8.32
				(4.86)
High	6.64	11.20	14.49	7.85
				(3.98)
High-Low	**-5.16**	**-3.42**	**-4.41**	
	(-2.97)	(-2.24)	(-2.95)	

Panel B: TFP and Size				
TFP	Small	Medium	Big	Big-Small
Low	22.83	13.02	9.51	-13.32
				(-4.68)
Medium	16.72	11.36	9.79	-6.94
				(-2.91)
High	14.90	9.64	8.06	-6.84
				(-2.77)
High-Low	**-7.93**	**-3.38**	-1.45	
	(-4.29)	(-1.88)	(-0.96)	

Panel C: TFP and Age				
TFP	Young	Medium	Old	Old-Young
Low	16.50	16.61	12.03	-4.47
				(-1.96)
Medium	13.37	13.56	10.87	-2.50
				(-1.38)
High	11.37	11.58	9.68	-1.69
				(-0.77)
High-Low	**-5.13**	**-5.03**	**-2.34**	
	(-2.89)	(-2.98)	(-1.80)	

Table 4: Excess Returns of Double Sorted Portfolios

2.3.2 Fama-MacBeth Regressions

We run Fama-MacBeth cross-sectional regressions (Fama and MacBeth, 1973) of monthly stock returns on lagged firm level TFP as well as other control variables and provide results for the full sample period and across two sub-periods of equal size in order to examine the stability and potential changes of the relationships over time. The estimates of the slope coefficients in Fama-MacBeth regressions allow us to determine the magnitude of the effect of the firm characteristics on excess stock returns.

Table 5 reports the time series averages of cross-sectional regression slope coefficients and their time-series t-statistic (computed as in Newey-West with 4 lags) obtained from the Fama-MacBeth regressions for the entire sample as well as for two sub samples. In all specifications, the dependent variable is the excess monthly stock returns, annualized to make the magnitudes comparable to the results in Table 2.

The first specification in Table 5 shows the relationship between TFP and future excess returns. The cross sectional regression, where log TFP is the only explanatory variable, produces a negative and statistically significant average slope. The magnitude of the effect is significant as well. The -6.11 average regression coefficient in this setting translates into approximately 3.5% higher expected returns for the firms in the lowest TFP decile compared to an average TFP firm.

Turning to the analysis of the return predictability over time, the last two rows of Table 5 report Fama-MacBeth regression results for the first and the second half of our sample periods separately. Productivity is negatively related to future stock returns in both sub-periods; the results are significant in both periods.

Fama-MacBeth Regressions

Dependent Variable: Excess Returns

	Intercept	**TFP**
1973:7-2007:6	12.61	-6.11
	(3.43)	(-3.11)
1973:7-1990:6	11.12	-6.89
	(1.96)	(-2.18)
1990:7-2007:6	14.10	-5.32
	(3.01)	(-2.28)

Table 5: Fama-MacBeth Regressions

In Table 6, we examine the marginal predictive power of TFP after controlling for several firm level characteristics that are known to predict stock returns and/or found to systematically vary with TFP in Table 1.

Fama-MacBeth Regressions
Dependent Variable: Excess Returns

	Int	TFP	BM	SIZE	IK	HR	INV	AG	PR	NS	LEV	AGE
I	10.09	0.22	3.10	-1.67								
	(3.25)	(0.18)	(2.67)	(-3.18)								
II	13.56	-4.76			-6.43							
	(4.02)	(-2.27)			(-1.84)							
III	12.97	-4.37				-7.92						
	(3.63)	(-2.28)				(-5.96)						
IV	13.18	-4.67					-4.25					
	(3.69)	(-2.35)					(-5.04)					
V	13.93	-3.12						-9.23				
	(3.93)	(-1.66)						(-7.04)				
VI	12.82	-5.03							-3.07			
	(3.42)	(-2.74)							(-2.29)			
VII	12.45	-6.25								-3.79		
	(3.40)	(-3.15)								(-3.20)		
VIII	11.01	-4.57									5.96	
	(3.01)	(-2.77)									(1.45)	
IX	14.83	-6.46										-0.14
	(3.08)	(-3.14)										(-1.68)
X	11.45	3.55	2.09	-1.73	-3.46	-1.28	-2.05	-3.42	-1.20	-8.23	-1.19	0.01
	(3.13)	(2.67)	(2.09)	(-4.00)	(-1.06)	(-0.93)	(-2.39)	(-2.43)	(-0.96)	(-3.02)	(-0.36)	(0.27)

Table 6: Fama-MacBeth Regressions with Other Predictors

In specifications I-IX, we add one firm characteristic at a time to the Fama-MacBeth regressions. Specification (I) considers firm's B/M and size, (II) considers investment to capital ratio, (III) considers hiring rate, (IV) considers inventory growth, (V) considers asset growth, (VI) considers profitability[14], (VII) considers net share issues, (VIII) considers leverage, and (IX) considers firm age. The definitions of these variables are available in Appendix, Section 5.1. In the last specification, X, we consider all the return predictors jointly. We include these return predictors in addition to our productivity variable as it is relatively standard to control for most of these variables in such predictability regressions. However, it is not clear that these are the right control variables in our setting. As we will discuss in Section 3, our model generates cross sectional varia-

[14]An alternative measure of profitability from Novy-Marx (2010), based on gross profits, produces starkly different Fama-MacBeth estimates. We find that TFP is negatively and significantly related to excess returns, whereas profitability based on gross profits is positively and significantly related to excess returns.

tions in characteristics such as B/M, size, hiring rate, and investment rate as a result of differences in firm level productivity (though the relationship does not have to be linear as assumed in the Fama-MacBeth regressions). To the extent that our model is valid, and the variables of interest are correctly measured, many of these variables should all be correlated. With this caveat in mind, we summarize the findings. We observe that the cross sectional regressions in specifications I to IX produce negative and statistically significant average slopes for TFP except for the specifications in I, and V where including book to market and size (in I), and asset growth (in V) erodes the significance of TFP.

The model considered here predicts that the information content of firm productivity is highly correlated with the information content of the firm characteristics examined previously. In order to understand the effect of TFP and components of other variables that are uncorrelated to TFP on returns, we orthogonalize the firm characteristics by taking the residuals from cross sectional regressions of firm characteristics on TFP and running orthogonalized Fama-MacBeth regressions. The results presented in Table 7 demonstrate that while TFP is uniformly related to future stock returns for the whole sample, the relationship is not significant in the first sub-sample of 1973 to 1990. In the second sub-sample, TFP is both economically and statistically significant, while size is the only other firm characteristic that remains significant in that period.

Orthogonalized Fama-MacBeth Regressions
Dependent Variable: Excess Returns

	Int	TFP	BM	SIZE	IK	HR	INV	AG	PR	NS	LEV	AGE
1973:7-2007:6	13.05	-5.02	2.09	-1.73	-3.46	-1.28	-2.05	-3.42	-1.20	-8.23	-1.19	0.01
	(3.61)	(-2.59)	(2.09)	(-4.00)	(-1.06)	(-0.93)	(-2.39)	(-2.43)	(-0.96)	(-3.02)	(-0.36)	(0.27)
1973:7-1990:6	11.78	-4.85	2.54	-1.80	-7.91	1.12	-1.92	-4.57	-0.46	-14.77	-0.08	0.10
	(2.10)	(-1.55)	(1.52)	(-2.74)	(-1.77)	(0.62)	(-1.78)	(-1.93)	(-0.22)	(-3.56)	(-0.02)	(1.71)
1990:7-2007:6	14.32	-5.20	1.64	-1.67	1.00	-3.68	-2.17	-2.26	-1.94	-1.69	-2.29	-0.07
	(3.13)	(-2.24)	(1.51)	(-2.93)	(0.22)	(-1.81)	(-1.63)	(-1.51)	(-1.44)	(-0.52)	(-0.40)	(-0.88)

Table 7: Orthogonalized Regressions

2.3.3 Ex-Ante Discount Rates of TFP-Sorted Portfolios

Both the portfolio approach and the Fama-MacBeth regressions reported in the previous section proxy expected returns with ex-post realized returns. A common concern about approximating expected returns with realized returns is that the realized returns are very volatile and can be a bad proxy for expected returns, especially with relatively short time series data. To address this concern, we use an ex-ante measure of the discount rate, the implied cost of capital of Hou, van Dijk, and Zhang (2010) and examine their cross-sectional relationship with TFP.

The implied cost of capital (ICC) of a given firm is the internal rate of return that equates the firm's stock price to the present value of expected future cash flows (earnings forecasts). Most ICC estimates in the literature (e.g., Gebhardt, Lee, and Swaminathan, 2001) rely on analyst forecasts of future earnings. However analyst forecasts are not available in the first few years of our sample period, and earnings forecasts of many firms in our sample are not available. Hou, van Dijk, and Zhang (2010) use a statistical model to forecast earnings, hence are not constrained by the analyst coverage of firms.

ICC for each firm is estimated at the end of June of each calendar year t using the end-of-June market value and the earnings forecasts at the previous fiscal year end. We match the ICC estimates of individual firms with these firms' most recent total factor productivity estimates. Higher risk of low TFP firms would imply higher ICC estimates for these firms.

Table 8 presents the average implied cost of capital estimates for portfolios sorted on productivity. The relationship between TFP and the cost of capital is negative and quite monotonic. The firms with low productivity have contemporaneously higher discount rates (ICC) than firms with high productivity: 13.79% versus 10.11% per annum. The spread of 3.68% is highly significant, implying that firms with low productivity have higher ex-ante discount rates, hence are riskier than high productivity firms. Furthermore, similar to the results based on average realized returns in Table 2, both the levels of implied cost of capital, and the spread between the low and high TFP portfolios are countercyclical. The spread between the discount rates of low and high TFP portfolios increases from 3.47% to 5.49% as the economy moves from expansions to contractions, as defined by the NBER. During recessions, firms with low productivity are hit particularly hard and thus bear more risk than firms with high TFPs.

Implied Cost of Capital of TFP Sorted Portfolios

	TFP Decile										
	Low	2	3	4	5	6	7	8	9	High	**High-Low**
All states	13.79	14.29	13.62	12.96	12.70	12.10	11.75	11.48	10.95	10.11	-3.68
											(-10.86)
Expansion	13.46	14.08	13.38	12.74	12.40	11.89	11.51	11.24	10.71	9.99	-3.47
											(-9.38)
Contraction	16.86	16.31	16.00	15.15	15.31	14.15	14.01	13.68	13.25	11.37	-5.49
											(-6.93)

Table 8: Implied Cost of Capital of TFP Sorted Portfolios

3 Model

The purpose of our theoretical model is to investigate the relationship between the firm's productivity and its characteristics and expected returns. The economy is populated with many competitive firms that take the stochastic discount factor (pricing kernel) and the stochastic wage rate as given. We pair this model of production with an exogenous pricing kernel that firms use to discount future cash flows, following Berk, Green, and Naik (1999); Zhang (2005); and Gomes and Schmid (2010) and a stochastic wage rate process. Since our focus is in understanding the cross sectional variation among firms, we take the time series properties of the pricing kernel as given.

3.1 Firms

There are many firms that produce a homogeneous good using capital and labor. These firms are subject to different productivity shocks.

The production function for firm i is given by:

$$\begin{aligned} Y_{it} &= F(A_t, Z_{it}, K_{it}, L_{it}) \\ &= A_t Z_{it} K_{it}^{\alpha_k} L_{it}^{\alpha_l}. \end{aligned}$$

K_{it} denotes the beginning of period t capital stock of firm i. L_{it} denotes the labor used in production by firm i during period t. Labor and capital share are given by α_l, and α_k where $\alpha_l + \alpha_k \in (0,1)$. Aggregate productivity is denoted by $a_t = \log(A_t)$. a_t has a stationary and monotone Markov transition function, given by $p_a(a_{t+1}|a_t)$, as follows:

$$a_{t+1} = \rho_a a_t + \varepsilon^a_{t+1} \tag{1}$$

where $\varepsilon^a_{t+1} \sim$ i.i.d. $\mathrm{N}(0, \sigma_a^2)$. The firm productivity, $z_{it} = \log(Z_{it})$, has a stationary and monotone Markov transition function, denoted by $p_{z_i}(z_{i,t+1}|z_{it})$, as follows:

$$z_{i,t+1} = \rho_z z_{it} + \varepsilon^z_{i,t+1} \tag{2}$$

where $\varepsilon^z_{i,t+1} \sim$ i.i.d. $\mathrm{N}(0, \sigma_z^2)$. $\varepsilon^z_{i,t+1}$ and $\varepsilon^z_{j,t+1}$ are uncorrelated for any pair (i,j) with $i \neq j$.

The capital accumulation rule is

$$K_{i,t+1} = (1-\delta)K_{it} + I_{it}$$

where I_{it} denotes investment and δ denotes the depreciation rate of installed capital.

Investment is subject to quadratic adjustment costs given by g_{it},

$$g(I_{it}, K_{it}) = \frac{1}{2}\eta\left(\frac{I_{it}}{K_{it}} - \delta\right)^2 K_{it} \tag{3}$$

with $\eta > 0$. In this specification, investors incur no adjustment cost when net investment is zero, i.e., when the firm replaces its depleted capital stock and maintains its capital level.

Firms are equity financed and face a perfectly elastic supply of labor at a given stochastic equilibrium real wage rate W_t as in Bazdresch, Belo, and Lin (2010). The equilibrium wage rate is assumed to be increasing with aggregate productivity

$$W_t = exp(a_t). \tag{4}$$

Hiring decisions are made after firms observe the productivity shocks and labor is adjusted freely; hence, for each firm, marginal product of labor equals the wage rate,

$$\begin{aligned} F_{L_{it}} &= F_L(A_t, Z_{it}, K_{it}, L_{it}) \\ &= W_t. \end{aligned}$$

Dividends to shareholders are equal to

$$D_{it} = Y_{it} - [I_{it} + g_{it}] - W_t L_{it}. \tag{5}$$

At each date t, firms choose $\{I_{i,t}, L_{i,t}\}$ to maximize the net present value of their expected dividend stream,

$$V_{it} = \max_{\{I_{i,t+k}, L_{i,t+k}\}} E_t \left[\sum_{k=0}^{\infty} M_{t,t+k} D_{i,t+k} \right], \tag{6}$$

subject to (Eq.1-4), where $M_{t,t+k}$ is the stochastic discount factor between time t and $t+k$. V_{it} is the cum-dividend value of the firm.

The pricing equations for the firm's optimization problem are:

$$1 = \int \int M_{t,t+1} R^I_{i,t+1} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a \tag{7}$$

where the returns to investment are given by

$$R^I_{i,t+1} = \frac{F_{K_{i,t+1}} + (1-\delta) q_{i,t+1} + \frac{1}{2}\eta \left(\left(\frac{I_{i,t+1}}{K_{i,t+1}} \right)^2 - \delta^2 \right)}{q_{it}} \tag{8}$$

and where

$$F_{K_{it}} = F_K(A_t, Z_{it}, K_{it}, L_{it}).$$

Tobin's q, the consumption good value of a newly installed unit of capital, is

$$q_{it} = 1 + \eta \left(\frac{I_{it}}{K_{it}} - \delta \right). \tag{9}$$

The returns to the firm are defined as

$$R^S_{i,t+1} = \frac{V_{i,t+1}}{V_{it} - D_{it}}.$$

3.2 The Stochastic Discount Factor

Following Berk, Green, and Naik (1999) and Zhang (2005), we directly parameterize the pricing kernel without explicitly modeling the consumer's problem. We follow Jones and

Tuzel (2010b) and modify the pricing kernel specification in Zhang (2005) as

$$\begin{aligned}\log M_{t+1} &= \log\beta - \gamma_t \epsilon^a_{t+1} - \frac{1}{2}\gamma_t^2\sigma_a^2 \\ \log\gamma_t &= \gamma_0 + \gamma_1 a_t\end{aligned}$$

where β, $\gamma_0 > 0$, and $\gamma_1 < 0$ are constant parameters.

Our model shares a number of similarities with Zhang (2005). M_{t+1}, the stochastic discount factor from time t to $t+1$, is driven by ϵ^a_{t+1}, the shock to the aggregate productivity process in period $t+1$. The volatility of M_{t+1} is time-varying, driven by the γ_t process. As in Zhang, this volatility takes higher values following business cycle contractions and lower values following expansions, implying a countercyclical price of risk as the result.[15] In the absence of countercyclical price of risk, the risk premia generated in the economy does not change with economic conditions. Empirically, existence of time varying risk premia is well documented (Fama and Schwert, 1977; Fama and Bliss, 1987; Fama and French, 1989; Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005; Jones and Tuzel, 2010a; among many others). Our empirical results in Table 2 and Table 8, that average (future) realized returns and implied cost of capital are much higher in contractions, compared to expansions, provide additional motivation for modeling countercyclical price of risk.

Two differences with Zhang (2005) are worth noting. One is that the riskless rate is constant in our specification. This follows the inclusion of the term $-\frac{1}{2}\gamma_t^2\sigma_a^2$ in the pricing kernel. This ensures that the pricing kernel has a constant expectation and implies that the riskless rate is equal to $-\log\beta$ in every period. The second difference is the exponential rather than linear specification of γ_t. The exponential guarantees positivity of γ_t, which prevents the relationship between M_{t+1} and ϵ_{t+1} from becoming perversely positive for high values of a_t.

3.3 Calibration and Quantitative Results

Solving our model generates solutions for firms' investment and hiring decisions as functions of the state variables, which are the aggregate and firm level productivity and the capital of the firm. Since the stochastic discount factor and the wages are specified exogenously, the solution does not require aggregation. Hence, the distribution of the capital stock, a high dimensional object is not in the state space. Our primary interest is in understanding the relationship between firm level productivity, firm characteristics, and expected returns.

[15] A countercyclical price of risk is endogenously derived in Campbell and Cochrane (1999) from time varying risk aversion; in Barberis, Huang, and Santos (2001) from loss aversion; in Constantinides and Duffie (1996) from time varying cross sectional distribution of labor income; in Barberis, Shleifer, and Vishny (1998) from time varying investor sentiment; in Guvenen (2009) from limited participation; in Bansal and Yaron (2004) from time varying economic uncertainty; and in Piazzesi, Schneider, and Tuzel (2007) from time varying consumption composition risk.

We calibrate the model at quarterly frequency but report annualized moments to match our annual empirical results. Table 9 presents the parameters used in the calibration, which correspond to quarterly frequency. We derive the parameters of the firm level productivity process from the production function estimations in Section 5.2. The persistence of the firm productivity process, ρ_z, is 0.915 ($= 0.7^{\frac{1}{4}}$). The conditional volatility of firm productivity, σ_z, is computed from ρ_z and the cross sectional standard deviation of firm productivity as 0.121 $\left(= 0.34 \times \sqrt{1 - 0.7^2} \times 0.5\right)$.[16] The parameters of the production function, α_k and α_l, are roughly equal to our estimates presented in Section 5.2. Even though our production function estimates imply an almost constant returns to scale production technology, we model technology as slightly decreasing returns to scale, with $\alpha_k + \alpha_l = 0.96$. It is well known that firm size is indeterminate with constant returns to scale technology. Decreasing returns to scale technology makes studying the relationship between firm size and productivity possible.

We take the parameters of the aggregate productivity from King and Rebelo (1999). Their point estimates for σ_a and ρ_a are 0.979 and 0.0072, respectively, using quarterly data. The depreciation rate for fixed capital is set to eight percent annually ($\delta = 0.02$ quarterly), which is roughly the midpoint of values used in other studies. Cooley and Prescott (1995) use 1.6%; Boldrin, Christiano, and Fisher (2001) use 2.1%; and Kydland and Prescott (1982) use a 2.5% quarterly depreciation rate.

We choose the pricing kernel parameters β, γ_0, and γ_1 to match the average riskless rate and the first two moments of aggregate excess stock returns measured from the data used in our empirical exercise. The discount factor β is 0.995, which implies an annual risk free rate of 2%. γ_0 and γ_1 are 4.12 and -7.10, respectively, and generate annual excess mean returns and standard deviation of 12.9% and 20.5%, respectively. Finally, the adjustment cost parameter, η, is set to 43 to replicate the average (annual) volatility of investment to capital ratio of 0.107 in our data.

Table 9: Model Parameter Values

Parameter	Description	Value
α_k	Capital share	0.17
α_l	Labor share	0.79
β	Discount factor	0.995
γ_0	Constant price of risk parameter	4.12
γ_1	Time varying price of risk parameter	-7.1
δ	Capital depreciation rate	0.02
η	Adjustment cost parameter	43
ρ_a	Persistence of aggregate productivity	0.98
σ_a	Conditional volatility of aggregate productivity	0.007
ρ_z	Persistence of firm productivity	0.915
σ_z	Conditional volatility of firm productivity	0.121

[16] The dispersion of firm productivity rises over time, from 0.23 in 1973 to 0.47 in 2005. In this calibration, we take the cross sectional standard deviation to be 0.34, which is the average dispersion over this time period.

Table 10 presents the average firm characteristics and expected returns for TFP sorted portfolios using simulated data from the model economy. The results indicate that the model is able to match the data presented in Table 1 and Table 2 reasonably well. The parameters of the firm level TFP process are taken from the empirical estimates, so it is not surprising that the average TFP of the simulated portfolios are matched almost exactly to the data. However, the model is not calibrated to match the cross section of the remaining characteristics, namely the investment to capital ratio, the hiring rate, firm size, book to market ratio, and the expected returns. We find that the investment to capital ratio and hiring rate both increase monotonically with TFP. However, the magnitude of the dispersion is higher than the dispersion in the data.[17] TFP is also monotonically and positively related to size and negatively related to B/M. The model is quite successful in matching the magnitude of the dispersion in size and B/M observed in the data, where the magnitudes are matched almost exactly. These results confirm that the model can qualitatively, and to a significant extent quantitatively, generate the relationship between productivity and these firm characteristics found in the data.

Table 10 also reports that the expected returns of TFP sorted portfolios decline monotonically with TFP. The spread in expected returns, −15.6%, is somewhat higher than the empirical spread of 4.90%(6.6% for the 10-2 portfolio) reported in Table 2. However, consistent with our empirical findings, both the average expected returns and the spread between the low and high TFP portfolio returns are much higher in contractions, compared to expansions. For this exercise, we define periods where aggregate productivity is more than one standard deviation lower than the mean as contractions, and the remaining periods as expansions. This definition leads to designating roughly 15% of the sample period as contractions, which is in line with the frequency of contractionary periods in the data (48 out of 408 months in our sample period). The model generates approximately 11.7% expected average returns, and 14.3% spread in TFP sorted portfolios in expansions (9.9% and 3.8% in the data, respectively), whereas the average returns are approximately 22.8%, and the spread is 27% in contractions (35.3% and 13.3% in the data).

[17] Both the dispersion in I/K and the hiring rate are somewhat higher than the dispersion in the data. The model-generated dispersion in I/K is approximately twice as high as the dispersion in the data. However, the model overshoots the dispersion in hiring rate significantly more. This problem could be alleviated by introducing adjustment costs in hiring/firing, which is currently assumed to be costless. Adjustment costs in hiring would reduce the volatility in hiring rate, hence reduce the dispersion in the hiring rate of the most productive and least productive firms.

Table 10: Model Implied Characteristics and Excess Returns
of TFP Sorted Portfolios (annualized)

	Low	2	3	4	5	6	7	8	9	High	H-L	
											Model	Data
TFP	0.60	0.70	0.82	0.90	0.97	1.04	1.13	1.23	1.37	1.70	1.10	1.22
Inv/K	-0.14	-0.05	-0.01	0.02	0.05	0.09	0.12	0.17	0.23	0.40	0.54	0.23
Hiring	-0.91	-0.55	-0.40	-0.22	-0.07	0.09	0.25	0.45	0.68	1.31	2.22	0.22
Size	0.27	0.37	0.47	0.56	0.67	0.80	0.97	1.21	1.62	3.05	2.78	2.72
B/M	1.57	1.49	1.39	1.27	1.18	1.10	1.01	0.93	0.85	0.75	-0.82	-0.95
						Future Returns						
Return	22.14	17.70	15.56	14.09	12.84	11.70	10.62	9.52	8.26	6.51	-15.63	-4.90
std	30.21	25.56	23.33	22.10	21.49	20.41	19.48	18.29	18.07	17.10	22.62	12.87
Expansions:												
Return	20.12	16.12	14.18	12.83	11.69	10.65	9.66	8.65	7.49	5.84	-14.28	-3.78
std	28.57	24.40	22.47	21.36	20.66	19.65	18.56	17.94	17.67	16.00	21.41	12.81
Contractions:												
Return	39.20	31.11	27.31	24.73	22.50	20.61	18.75	16.89	14.85	12.15	-27.05	-13.36
std	40.26	32.77	29.38	26.79	26.15	25.03	25.32	20.75	20.52	19.77	30.68	13.22

In this economy, aggregate productivity shocks drive the business cycles. In bad times (low aggregate productivity), net present value of investments go down due to lower expected cash flows. Hence, all firms would like to invest less and hire less. Even though they can freely adjust their labor[18], they incur adjustment costs when they change their capital stock. Firms with low firm level productivity are particularly burdened with unproductive capital, finding it more difficult to reduce their capital stocks than the firms with high productivity. Since the price of the installed capital, Tobin's q (given in Eq. 9), is an increasing function of their investment to capital ratio, their value goes down. Therefore, the returns of the low TFP firms covary more with economic downturns. The opposite is true in expansions.[19]

This mechanism is complemented with the countercyclical price of risk. We assume that the volatility of the pricing kernel is a decreasing function of aggregate productivity; hence, discount rates are higher in bad times. Since risk is defined as the covariation with the pricing kernel, everything else equal, higher volatility of the pricing kernel implies

[18] This is an assumption to keep the model as simple as possible. Bazdresch, Belo, and Lin (2010) consider an economy with labor adjustment costs, in addition to the usual capital adjustment costs, and find qualitatively similar results.

[19] For simplicity, we assume symmetric adjustment costs; hence, firms incur similar adjustment costs while increasing or decreasing the capital stock. Zhang (2005) and Tuzel (2010) use asymmetric adjustment costs, where reducing the capital stock is more costly than making new investment. This asymmetry in adjustment costs leads to asymmetry in the covariation of low and high TFP firms' returns with the business cycles: Returns of low productivity firms covary more with economic downturns then the covariation of high TFP firms' returns with economic upturns. This mechanism would strengthen our results.

higher covariation with the kernel, hence higher risk in bad times, especially for the low TFP firms. Countercyclical price of risk leads to even lower net present values for firms in recessions, especially firms with low productivity. Hence, low TFP firms want to invest even less (or disinvest even more) in bad times.

Without the countercyclical price of risk, the model could neither generate the average level of risk premia nor the spread between the returns of the high and low TFP firms. However, the model that is calibrated to match the average level and volatility of the risk premia (through the calibration of the pricing kernel) is capable of matching many of the cross sectional properties, including the spread between the returns of the TFP sorted portfolios.

4 Conclusion

This paper examines the relationship between firm level TFP and certain firm characteristics and returns. We find that high TFP firms are typically large growth firms. The hiring rate, fixed investment to capital ratio, asset growth, and inventory growth are all monotonically increasing in firm level TFP. We also show that TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future returns, as well as ex-ante discount rates. The unconditional return spread is sizable, approximately 5% in realized returns and 4% in implied cost of capital. However, there is significant variation in the spread over the business cycles; the spread is almost three times as high during NBER contractions as it is during expansions. We interpret the spread in the average returns across these portfolios as the risk premia associated with the higher risk of low productivity firms. We show that a production-based asset pricing model with aggregate and idiosyncratic shocks is able to account for most of these stylized facts quantitatively.

While our results are stronger for smaller firms, it is important to point out that these firms collectively make up a very significant fraction of employment and output in the manufacturing sector. In addition, they have large contributions to economic fluctuations in the aggregate data. Our investigation points out that the TFP shocks faced by large firms are significantly more persistent than that of the small firms. This difference in the persistence leads to differences in many dimensions such as the hiring rate, investment to capital ratio, asset growth, and stock returns. Examining the likely reasons for the high persistence of productivity in big firms is left for future research.

References

[1] Atkeson, A. and Kehoe, P. J. (2005). "Modeling and Measuring Organization Capital." *Journal of Political Economy* 113(5): 1026-1053.

[2] Baily, M. N., Hulten, C. and Campbell, D. (1992). "The Distribution of Productivity in Manufacturing Plants." Brookings Papers on Economic Activity: Microeconomics, Washington, D.C., pp.187-249.

[3] Ball, R. (1978). "Anomalies in Relationships Between Securities' Yields and Yield Surrogates." *Journal of Financial Economics* 6: 103–126.

[4] Bansal, R. W. and Yaron, A. (2004). "Risks For the Long Run: A Potential Resolution of Asset Pricing Puzzles." *Journal of Finance* 59, 1481-1509

[5] Banz, R. W. (1981). "The Relationship Between Return and Market Value of Common Stocks." *Journal of Financial Economics* 9: 3–18.

[6] Barberis, N., Shleifer, A. and Vishny, R. (1998), "A Model of Investor Sentiment." *Journal of Financial Economics* 49, 307-343,

[7] Barberis, N., Huang, M. and Santos, T. (2001). "Prospect Theory and Asset Price." *Quarterly Journal of Economics* 116, 1-53.

[8] Bartelsman, E. J. and Doms, M. (2000). "Understanding Productivity: Lessons from Longitudinal Microdata." *Journal of Economic Literature* 38, 569-594.

[9] Bartelsman, E. J. and Dhrymes, P. J. (1998). "Productivity Dynamics: U.S. Manufacturing Plants 1972-1986." *Journal of Productivity Analysis.*, 9:1 pp. 5-34.

[10] Basu, S. (1983). "The Relationship Between Earnings Yield, Market Value, and Return for NYSE Common Stocks: Further evidence." *Journal of Financial Economics* 12, 129–156.

[11] Bazdresch, S. Belo, F., and X. Lin (2010). "Labor Hiring, Investment and Stock Return Predictability in the Cross Section". Working paper.

[12] Belo, F. and X. Lin (2010). "The Puzzling Inventory Growth Risk Premium ". Working paper.

[13] Berk, J. B., Green, R. C. and Naik, V. (1999). "Optimal Investment, Growth Options, and Security Returns." *Journal of Finance* 54, 1553-1607.

[14] Bhandari, L. (1988). "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence, *Journal of Finance* 43, 507-28.

[15] Boldrin, M., Christiano, L. and Fisher, J. (2001). "Habit Persistence, Asset Returns, and the Business Cycle." *American Economic Review* 91, 149-166.

[16] Brynjolfsson, E. and Hitt, L. (2003) "Computing Productivity: Firm-Level Evidence." *Review of Economics and Statistics*, 85 (4), 793-808.

[17] Campbell, J.Y. and Cochrane, J.H., (1999). "By force of habit: a consumption-based explanation of aggregate stock market behavior." *Journal of Political Economy* 107, 205–251.

[18] Campbell, J., and Shiller, R. (1991). "Yield Spreads and Interest Rate Movements: A Bird's Eye View." *Review of Economic Studies* 58, 495-514.

[19] Campbell, J., M. Lettau, B. G. Malkiel, and Y. Xu. (2001). "Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk." *Journal of Finance* 56,1–43.

[20] Chan, L. K.C., N. Jegadeesh, and J. Lakonishok (1996), "Momentum Strategies", *Journal of Finance* 51, 1681-1713.

[21] Cochrane, J. H., and Piazzesi, M. (2005). "Bond Risk Premia," *American Economic Review* 95, 138-160.

[22] Constantinides, G., Duffie, D. (1996). "Asset Pricing with Heterogeneous Consumers." *Journal of Political Economy* 104, 219–240.

[23] Cooley, T. F., and Prescott, E. C. (1995). "Economic Growth and Business Cycles." Frontiers of Business Cycle Research, (Thomas F. Cooley, editor), Princeton University Press.

[24] Cooper, I., Gulen, H. and Schill, M. (2008). "Asset Growth and the Cross-Section of Stock Returns." *Journal of Finance* 63, 1609-1652.

[25] Corrado, C., Hulten C.R., and Sichel D. E. (2005). "Measuring Capital and Technology: An Expanded Framework", in C. Corrado, J. Haltiwanger and D. Sichel (eds.) Measuring Capital in the New Economy (Chicago, Chicago University Press).

[26] De Bondt,W. F. M., and R. Thaler (1985). "Does the Stock Market Overreact?" *Journal of Finance* 40, 793–805.

[27] Dwyer, D. (1997). "Technology Locks, Creative Destruction, and Non-Convergence in Productivity Levels." New York University working paper.

[28] Eisfeldt, L. A. and Papanikolaou, D. (2009). "Organization Capital and the Cross-Section of Expected Returns." Working paper.

[29] Evenson, R.E. and Westphal, L.E. (1995). "Technological Change and Technological Strategy." In J. Behrman and T.N. Srinivasan, eds., Handbook of Development Economics. Amsterdam, North-Holland.

[30] Fama, E., and Bliss, R.(1987). "The Information in Long-Maturity Forward Rates." *American Economic Review* 77, 680-692.

[31] Fama, E., and French, K. (1989). "Business Conditions and Expected Returns on Stocks and Bonds." *Journal of Financial Economics* 25, 23-49.

[32] Fama, E. F. and French, K. (1992). "The cross section of expected stock returns." *The Journal of Finance* 47, 427-465.

[33] Fama, E. F. and K. R. French. (1993). "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33, 3-56.

[34] Fama, E. F. and K. R. French. (2008). "Dissecting anomalies." *Journal of Finance* 63, 1653-1678.

[35] Fama, E. F. and J. D. MacBeth. (1973). "Risk, return, and equilibrium: Empirical tests." *Journal of Political Economy* 81, 607-636.

[36] Fama, E., and Schwert, W. (1977). "Asset Returns and Inflation." *Journal of Financial Economics* 5, 115-146.

[37] Gala, V. (2006). "Irreversible Investment and the Cross-Section of Stock Returns in General Equilibrium." Working paper.

[38] Gebhardt, W.R., C.M.C. Lee, and B. Swaminathan (2001). "Toward an Implied Cost of Capital." *Journal of Accounting Research,* 39, 135-176.

[39] Gomes, J. F. (2001). "Financing Investment." *American Economic Review* 90, 1263–1285.

[40] Gomes, J. F., Kogan, L. and Zhang, L. (2003). "Equilibrium Cross-Section of Returns." *Journal of Political Economy* 111, 693-732.

[41] Gomes, J. F. and Schmid, L. (2010), "Levered Returns", *Journal Finance*, Volume 65 Issue 2, Pages 467 - 494.

[42] Gourio, F. (2007). "Labor Leverage, Firms'Heterogeneous Sensitivities to the Business Cycle, and the Cross-Section of Expected Returns." Working paper. Boston University

[43] Gourio, F. (2008). "Estimating Firm-Level Risk." Working paper. Boston University.

[44] Hennessy, C. and T. Whited (2005). "Debt Dynamics." *Journal of Finance,* 60: 1129—1165.

[45] Guvenen, F., (2009). "A Parsimonious Macroeconomic Model for Asset Pricing." *Econometrica*, Vol 77, No 6, pp. 1711-1750.

[46] Hadlock, Charles J. and Joshua R. Pierce. (2010). "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index." *Review of Financial Studies* 23, pages 1909-1940.

[47] Hall, B. H. (1990). “The Manufacturing Sector Master File: 1959-1987.” NBER Working paper 3366.

[48] Hall, R. (2000). “e-Capital: The Link between the Stock Market and the Labor Market in the 1990s.” Brookings Papers on Economic Activity, 73-118.

[49] Hall, R. (2001). “The Stock Market And Capital Accumulation.” *American Economic Review* 91: 1185-1202.

[50] Hou, K., van Dijk, A. M., and Zhang, Y. (2010) “The Implied Cost of Capital: A New Approach.” Working paper.

[51] Hulten, C. R. (1990). “The Measurement of Capital,” in Ernst R. Berndt and Jack E. Triplett eds., *Fifty Years of Economic Measurement: The Jubilee of the Conference on Research in Income and Wealth*, NBER Studies in Income and Wealth Vol. 54, (Chicago: University of Chicago Press), pp. 119-152.

[52] Jegadeesh, N. and S. Titman (1993). “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency”. *Journal of Finance* 48, 65-91.

[53] Jones, C. S., and Tuzel, S. (2010a). “New Orders and Asset Prices.” Working paper, USC.

[54] Jones, C. S., and Tuzel, S. (2010b). “Inventory Investment and the Cost of Capital.” Working paper, USC.

[55] King, R. G. and Rebelo, S. T. (1999). “Resuscitating Real Business Cycles.” Handbook of Macroeconomics, in: J. B. Taylor & M. Woodford (ed.), Handbook of Macroeconomics, edition 1, volume 1, chapter 14, pages 927-1007 Elsevier.

[56] Kydland, F. and Prescott, E. (1982). “Time to Build and Aggregate Fluctuations.” Econometrica 50, 1345-1370.

[57] Lev, B., and S. Radhakrishnan (2005). “The Valuation of Organization Capital,” in Corrado, Haltiwanger, and Sichel, eds., Measuring Capital in a New Economy, National Bureau of Economic Research and University of Chicago Press, 73-99.

[58] Levinsohn, J. and A. Petrin (2003). “Estimating Production Functions Using Inputs to Control for Unobservables”, *Review of Economic Studies,* vol. 70, no. 2, pp. 317–341.

[59] Li, E. X. N., Livdan, D. and Zhang, L. (2009). “Anomalies.” Review of Financial Studies 22 (11), 4301-4334.

[60] Livdan, D., Sapriza, H. and Zhang, L. (2009). “Financially Constrained Stock Returns”, *Journal of Finance* 64, pages 1827-1862.

[61] Lyandres, E., Sun, L. and Zhang, L. (2008). “The New Issues Puzzle: Testing the Investment-Based Explanation.” *Review of Financial Studies* 21, 2825-55.

[62] McGrattan, E.R. and Prescott, E.C. (2005). "Taxes, Regulations, and the Value of U.S. and U.K. Corporations." *Review of Economic Studies* 72, 767-796.

[63] Novy-Marx, R. (2010)."The Other Side of Value: Good Growth and the Gross Profitability Premium." Working paper, University of Chicago.

[64] Olley, S. and Pakes, A. (1996). "The Dynamics Of Productivity In The Telecommunications Equipment Industry", *Econometrica* 64, 1263-1297.

[65] Piazzesi, M., Schneider, M. and Tuzel, S. (2007)."Housing, Consumption, and Asset Pricing." *Journal of Financial Economics* 83, 531-69.

[66] Sloan, R. G. (1996). "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?" *The Accounting Review* 71, 289-315.

[67] Syverson, C. (2004). "Product Substitutability and Productivity Dispersion." *Review of Economics and Statistics*, 86(2): 534-550.

[68] Thomas, J. K., and H. Zhang (2002). "Inventory Changes and Future Returns." *Review of Accounting Studies* 7, 163-87.

[69] Titman, S., Wei, K.C. J. and Xie, F. (2003). "Capital Investments and Stock Returns." *Journal of Financial and Quantitative Analysis* 39, 677-700.

[70] Tuzel, S. (2010). "Corporate Real Estate Holdings and the Cross Section of Stock Returns", *Review of Financial Studies* 23, 2268-2302.

[71] Wu, J., Zhang, L. and Zhang, F. (2010). "The q-theory Approach to Understanding the Accrual Anomaly." *Journal of Accounting Research* 48, 177-223.

[72] Zhang, L. (2005). "Value premium." *Journal of Finance* 60, 67-103.

5 Appendix: Measuring TFP

The main contributions to measuring firm level TFP are by Olley and Pakes (1996) and Levinsohn and Petrin (2003). The key difference between the two is that Olley and Pakes (1996) use investment whereas Levinsohn and Petrin (2003) use intermediate material as a proxy for TFP. Since data on investment is readily available and often non-zero at the firm level but data on materials is not, we follow Olley and Pakes (1996) to estimate firm level productivities. The major advantage of this approach over more traditional production function estimation techniques such as ordinary least squares (OLS) is its ability to control for selection and simultaneity biases and deal with the within firm serial correlation in productivity. The static OLS production function estimates reveal that within firm residuals, which are the productivity estimates in this setting, are serially correlated. The simultaneity bias arises if the firm's factor input decision is influenced by the TFP that is observed by the firm. This means that the regressors and the error term in an OLS regression are correlated, resulting in biased estimates of the production function parameters. The selection bias in the OLS regressions arises due to firms exiting the sample used in estimating the production function parameters. If the exit probability is correlated with productivity, not accounting for the selection issue may bias the production function parameter estimates.

In our benchmark case, we estimate the production function based on traditional inputs of labor and capital. In the more general case presented in this section, we extend the Olley and Pakes method to include organization capital as another input in the production function.[20] We proceed by discussing the estimation for the general case with organizational capital and provide the results for this case under sensitivity analysis in the next section.[21]

Assume that the production technology is represented by a production function that relates output to inputs and productivity, where we treat organization capital just as another input.

$y_{it} = F(l_{it}, k_{it}, oc_{it}, \omega_{it})$ where y_{it} is log output for firm i in period t. l_{it}, k_{it}, oc_{it} are log values of labor, physical capital, and organization capital of the firm. ω_{it} is the productivity. Specifically,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_{oc} oc_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}. \tag{10}$$

Following Eisfeldt and Papanikolaou (2009), the measure of organization capital is

[20] There is a large and growing literature on organizational capital (intangible capital) and its implications for the macroeconomy. See Hall (2000, 2001); Corrado, Hulten, and Sichel (2005); and McGrattan and Prescott (2005).

[21] Our results are not sensitive to alternative ways of measuring TFP, such as the inclusion of inventories in the definition of the capital stock, estimating the model with age as another variable, including R&D capital, using different deflators, or carrying out the estimation at the industry level.

constructed based on the perpetual inventory equation given by

$$\exp(oc_{it}) = (1-\delta)\exp(oc_{it-1}) + ioc_{it}$$

where ioc_{it} is the firm's investment in organization capital, as measured from the firm's reported sales, general, and administrative expenses, deflated using the price deflator for investment for the matching industry.[22] The depreciation rate for organization capital δ is set to 20% and the initial stock is chosen to equal the level of investment in organizational capital in the first year the firm appears in our data set. In our benchmark case, oc_{it} is set equal to zero.

Olley and Pakes assume that productivity, ω_{it}, is observed by the firm before the firm makes some of its factor input decisions, which gives rise to the simultaneity problem. Labor, l_{it}, is the only variable input, i.e., its value can be affected by current productivity, ω_{it}. The other inputs, k_{it} and oc_{it}, are fixed inputs at time t and their values are only affected by the conditional distribution of ω_{it} at time $t-1$. Consequently, ω_{it} is a state variable that affects firms' decision making where firms that observe a positive productivity shock in period t will invest more in physical capital, i_{it}, and in organizational capital, ioc_{it}, and hire more labor, l_{it}, in that period. The solution to the firm's optimization problem results in the equations for i_{it} and ioc_{it},

$$\begin{aligned} i_{it} &= i\left(\omega_{it}, k_{it}, oc_{it}\right) && (11)\\ ioc_{it} &= j\left(\omega_{it}, k_{it}, oc_{it}\right), && (12) \end{aligned}$$

where both i and j are strictly increasing in ω. The inversion of the equations yield

$$\omega_{it} = h(i_{it}, k_{it}, ioc_{it}, oc_{it})$$

where h is strictly increasing in i_{it} and ioc_{it}.

Define

$$\phi_{it} = \beta_0 + \beta_k k_{it} + \beta_{oc} oc_{it} + h(i_{it}, k_{it}, ioc_{it}, oc_{it}). \tag{13}$$

Using equations 10 and 13, we can obtain

$$y_{it} = \beta_l l_{it} + \phi_{it} + \eta_{it} \tag{14}$$

where we approximate ϕ_{it} with a second order polynomial series in physical and organizational capital and investment in physical and organizational capital.[23] This first stage estimation results in an estimate for $\widehat{\beta}_l$ that controls for the simultaneity problem.[24] In

[22] SGA includes IT expenditures, employee training costs, brand enhancement activities, payment to systems and strategy consultants, and the cost of setting up and maintaining internet-based supply and distribution channels. Of course, SGA is not the perfect measure since it may also include expenditures that do not constitute investment in organization capital. For a detailed discussion of the appropriateness of SGA as a measure of organization capital, see Lev and Radhakrishnan (2005).

[23] Approximating with a higher order polynomial instead does not significantly change the results.

[24] Since our data set covers all manufacturing industries with different market structures and factor prices we estimate equation 14 with industry specific time dummies.

the second stage, consider the expectation of $y_{i,t+1} - \widehat{\beta}_l l_{i,t+1}$ on information at time t and survival of the firm[25]:

$$E_t\left(y_{i,t+1} - \widehat{\beta}_l l_{i,t+1}\right) = \beta_k k_{i,t+1} + \beta_{oc} oc_{i,t+1} + E_t(\omega_{it+1}|\omega_{it}, survival) \tag{15}$$
$$= \beta_k k_{i,t+1} + \beta_{oc} oc_{i,t+1} + g(\omega_{it}, \widehat{P}_{survival,t})$$

where $\widehat{P}_{survival,t}$ denotes the probability of firm survival from time t to time $t+1$. The survival probability is estimated via a probit of a survival indicator variable on a polynomial expression containing physical and organizational capital and investment in physical and organizational capital. We fit the following equation by nonlinear least squares:

$$y_{i,t+1} - \widehat{\beta}_l l_{i,t+1} = \beta_k k_{i,t+1} + \beta_{oc} oc_{i,t+1} + \rho\omega_{it} + \tau\widehat{P}_{survival,t} + \xi_{i,t+1} + \eta_{i,t+1}$$

where ω_{it} is given by $\omega_{it} = \phi_{it} - \beta_0 - \beta_k k_{it} - \beta_{oc} oc_{it}$ and is assumed to follow an AR1 process. At the end of this stage, $\widehat{\beta}_l$, $\widehat{\beta}_k$ and $\widehat{\beta}_{OC}$ are estimated.

Finally, productivity is measured by

$$P_{it} = \exp(y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_{oc} oc_{it}).$$

5.1 Data

The key variables for estimating the firm level productivity in our benchmark case are the firm level value added, employment, and physical capital. In the sensitivity analysis, we also include a measure of organization capital. The firm level data is obtained from Compustat and supplemented by industry level data from the NBER-CES Manufacturing Industry Database.[26]

Value added (y_{it}) is computed as Sales - Materials, deflated by the price deflator for the value of shipments for the matching industry from the NBER-CES Manufacturing Industry Database (PISHIP). Sales is net sales from Compustat (SALE).[27] Materials is measured as Total expenses minus Labor expenses. Total expenses is approximated as [Sales - Operating Income Before Depreciation and Amortization (Compustat (OIBDP))]. Labor expenses is calculated by multiplying the number of employees from Compustat (EMP)

[25] We also take out the effects of industry specific time dummies at this stage.

[26] NBER-CES Database covers all 4-digit SIC and 6-digit NAICS manufacturing industries from 1958-2005. However, some industries enter or leave manufacturing in 1997 when the industry code changed from SIC to NAICS, so some industrys' observations are missing for 1958-1996 or 1997-2005. The industry designation of firms are taken form Compustat (SIC and NAICS codes). Compustat SIC codes are typically at the 4-digit level, however, sometimes Compustat reports SIC codes at 3-digit or 2-digit level (SIC codes where 3rd or 4rd digit are zero would correspond to lower level SIC codes). Compustat NAICS codes are more sparsely populated and can be at various levels. In matching the firm industries to the NBER-CES Database, the data is first matched using the 4-digit SIC codes. For firms where this match fails, the pairs are attempted to be matched using the NAICS codes. If this match also fails, we match the firms to the deflators and wages at the 2-digit SIC code level, where deflator and wage data from 4-digit SIC industries are aggregated to calculate their 2-digit SIC code counterparts.

[27] Net sales are equal to gross sales minus cash discounts, returned sales, etc.

by wages for the matching industry from the NBER-CES Database (PAY/EMP[28]).[29] The stock of labor (l_{it}) is measured by the number of employees from Compustat (EMP).

Capital stock (k_{it}) is given by gross Plant, Property & Equipment (PPEGT) from Compustat, deflated by the price deflator for investment for the matching industry from the NBER-CES Database (PIINV) following the methods of Hall (1990) and Brynjolfsson & Hitt (2003).[30] Since investment is made at various times in the past, we need to calculate the average age of capital at every year for each company and apply the appropriate deflator (assuming that investment is made all at once in year [current year - age]). Average age of capital stock is calculated by dividing accumulated depreciation (Gross PPE - Net PPE, from Compustat (DPACT)) by current depreciation, from Compustat (DP). Age is further smoothed by taking a 3-year moving average.[31] The resulting capital stock is lagged by one period to measure the available capital stock at the beginning of the period.

Organizational capital (oc_{it}) is calculated from the Sales, General, and Administrative Expenses from Compustat (XSGA). Following Eisfeldt and Papanikolau (2009), we construct the organizational capital by using the perpetual inventory method. Sales, general and administrative expenses are considered as investment in organizational capital, deflated by the price deflator for investment for the matching industry from the NBER-CES Database (PIINV) and assumed to depreciate by 20% per year.[32]

Our sample for production function estimation is comprised of all manufacturing firms that have positive data on sales, total assets, number of employees, gross plant property equipment, depreciation, accumulated depreciation, sales, general and administrative expenses, and capital expenditures. The sample period spans 1958-2005; however, there are relatively few observations in the early years of the sample. The sample is an unbalanced panel with approximately 5700 distinct firms; the total number of firm-year observations is approximately 71000.[33]

Fixed investment to capital ratio is given by firm level real capital investment di-

[28] EMP here is total employment at the industry level from the NBER-CES Database. The previous EMP was the number of employees at the firm level, taken from Compustat. Both databases use the same code.

[29] Compustat also has a data item called staff expense (XLR), which is sparsely populated. Comparing our labor expense series with the staff expense data available at Compustat reveals that our approximation yields a relatively correct and unbiased estimate of labor expenses.

[30] Hulten (1990) discusses many complications related to the measurement of capital. The principal options are to look for a direct estimate of the capital stock, K, or to adjust book values for inflation, mergers, and accounting procedures, or to use the perpetual inventory method. There are problems associated with either method and most of the time, the choice between these methods is dictated by the availability of data. Our results are insensitive to the treatment of inventories as a part of the capital stock.

[31] If there are less than three years of history for the firm, the average is taken over the available years.

[32] Following Atkeson and Kehoe (2005), Lev and Radhakrishnan (2005), and Evenson and Westphal (1995), organizational capital is viewed as a firm-specific capital good that is embodied in the organization itself.

[33] At this stage, we do not require the firms to be in CRSP database. Hence, our sample size gets somewhat smaller later when we merge our dataset with CRSP data.

vided by the beginning of the period real capital stock. Investment to capital ratio for organizational capital is obtained similarly. Asset growth is the percent change in total assets (TA) from Compustat. Hiring rate at time t is the change in the stock of labor from time $t-1$ to t. Inventory growth is the percent change in inventories (INVT) from Compustat. R&D/PPE is the research and development expenditures (XRD from Compustat) divided by gross plant property and equipment. Real estate ratio for each firm is calculated by dividing the real estate components of PPE (sum of buildings and capitalized leases) by total PPE. Firm size is the market value of the firm's common equity (number of shares outstanding times share price from Center for Research in Security Prices (CRSP)). B/M, net stock issues (NS), and Profitability (PR) are defined as in Fama and French (2008). Leverage is calculated by dividing long-term debt holdings (DLTT in Compustat) by firm's total assets calculated as the sum of their long-term debt and the market value of their equity. Firm age (AGE) is proxied by the number of years since the firm's first year of observation in Compustat.

5.2 Estimation and Properties of TFP

The estimates for the production function and the standard errors are given in Table A1. The results for the benchmark case presented in column two indicate a labor share of 0.826 and a capital share of 0.172. For the benchmark case, we also present results for different sized firms based on the average number of workers per firm. Small firms are those with less than 1600 employees. Medium firms are those in the 50th to 80th percentile (between 1600 and 8600 workers) and big firms are those with more than 8600 employees. Our results indicate that the share of labor declines with firm size. The estimates for the persistence and the standard deviation of the TFP shock, at the annual frequency, are 0.7 and 0.24 respectively for all the firms. The persistance increases with firm size. We also document an increase in the cross sectional dispersion of firm level productivity from 0.23 in 1973 to 0.47 in 2005. In the case with organizational capital, the share of labor and capital go down to 0.757 and 0.126 (from 0.826 and 0.172, respectively), and the share of organizational capital turns out to be 0.137.

Table A1: Production Function Parameters

	Benchmark				**With OC**
	All	Small	Medium	Large	All
Labor	0.826	0.891	0.781	0.744	0.757
	(0.002)	(0.005)	(0.006)	(0.005)	(0.003)
Capital	0.172	0.077	0.142	0.137	0.126
	(0.003)	(0.007)	(0.008)	(0.01)	(0.004)
Org. Capital					0.137
					(0.004)
Autocorrelation	0.700	0.703	0.758	0.971	0.700
	(0.01)	(0.018)	(0.02)	(0.01)	(0.007)

One method used in summarizing the evolution of productivity is the transition matrix, which shows the probability of a plant/firm moving from a certain productivity percentile in a period to other percentiles in the next period. Table A3 presents the transition probability matrix for the firms sorted into decile TFP portfolios in our sample for the benchmark case. The probabilities of staying in the lowest or the highest TFP portfolios are about 50%. The higher probabilities along the diagonal shows that there is some persistence in productivity. The table also reports the probability that a firm in a given portfolio will disappear from our sample in the next year. The drop-off may be the result of either firm failure or a missing data item in the following year. The probability of drop-off ranges from 13% for the firms in the lowest portfolio to 7% for the firms in the highest TFP portfolio. The negative relationship between drop-off rates and TFP shows that low probability firms are more likely to disappear from our sample where the difference in the drop-off rates can be interpreted as the higher likelihood for failure of low TFP firms. The results for the transition probabilities are very similar for the case with organizational capital.

Portfolio Transition Probabilities: 10 Portfolios sorted on TFP

		Year t										
		Low	2	3	4	5	6	7	8	9	High	Dropoff
	Low	**0.47**	0.19	0.07	0.04	0.03	0.02	0.02	0.01	0.01	0.01	0.14
	2	0.18	**0.30**	0.19	0.09	0.05	0.03	0.02	0.01	0.01	0.00	0.11
	3	0.07	0.18	**0.25**	0.18	0.10	0.06	0.03	0.02	0.01	0.01	0.10
	4	0.04	0.09	0.18	**0.23**	0.18	0.10	0.05	0.03	0.01	0.00	0.09
Year	5	0.03	0.06	0.10	0.17	**0.20**	0.17	0.10	0.05	0.02	0.00	0.09
(t-1)	6	0.02	0.03	0.06	0.11	0.17	**0.21**	0.18	0.09	0.03	0.01	0.08
	7	0.02	0.02	0.03	0.06	0.10	0.17	**0.23**	0.18	0.08	0.02	0.08
	8	0.02	0.02	0.02	0.04	0.06	0.10	0.19	**0.25**	0.17	0.04	0.08
	9	0.02	0.02	0.02	0.02	0.03	0.05	0.08	0.20	**0.34**	0.15	0.08
	High	0.02	0.01	0.01	0.01	0.01	0.02	0.03	0.06	0.17	**0.59**	0.08

Table A3: Portfolio Transition Probabilities

Various papers examine the persistence of productivity at the plant level. For example, Bartelsman and Dhrymes (1998) examine transition probabilities of plant level TFPs in three industries over 1972-1986.[34] They report a great deal of persistence where about 50 to 70% of the plants in the lowest and highest deciles tend to stay in the same bin for all the three industries. Their drop-off rates also decline with the TFP decile. Baily, Hulten, and Campbell (1992) reach similar conclusions in twenty three 4-digit SIC industries.

Lastly, we construct an aggregate productivity measure based on firm level productivities obtained earlier for our benchmark case and study its characteristics. First, we compute the average industry level TFP and find the industry level TFP growth rates.

[34] The industries examined are Machinery, except Electrical, Electrical and Electronic Equipment and Supplies, and Measuring Instruments.

Then, the industry level productivity growth rates are aggregated using an industry's share in total sales. In figure A1, the resulting aggregate TFP growth is compared with the industrial TFP growth rate provided by EU KLEMS Growth and Productivity Accounts (2009). The higher volatility produced by our data is somewhat expected since it provides an aggregation over a smaller number of firms compared to the EU KLEMS data. Nevertheless, the correlation between the two series is 0.8.

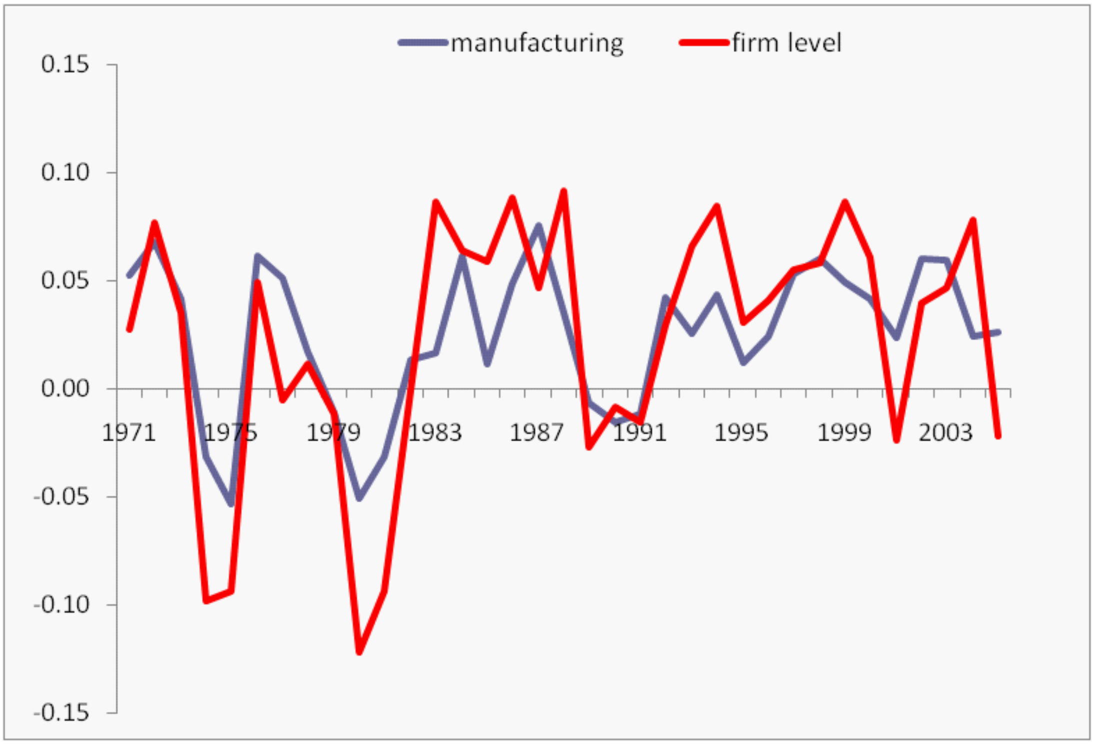

Figure A1: TFP Comparisons

Overall, we conclude that the firm level TFP series estimated using the Compustat data have reasonable properties.[35]

5.2.1 TFP Estimation and Results with Organizational Capital

In this section, we report some of the results for the production function with organizational capital. Table A4 provides the summary statistics, which are very similar to the benchmark case in most of the dimensions. As before, firms with low TFPs are small value firms. High TFP firms are growth firms.

[35] In another specification we computed firm level TFPs without using industry dummies. The industry TFP is formed as the simple average of log TFPs of the firms in that industry. Then we analyzed the industry adjusted TFPs of firms, which are the log TFPs in excess of their industry averages. The stylized facts generated from that framework is both qualitatively and quantitatively very similar to our benchmark results even though the production function estimates for labor and capital are 0.645 and 0.341 respectively.

	Low	2	3	4	5	6	7	8	9	High	High-Low
Summary Statistics: 10 Portfolios Sorted on TFP											
TFP	0.54	0.72	0.79	0.85	0.91	0.97	1.03	1.12	1.26	1.80	1.26
Size	0.24	0.59	0.81	0.89	1.12	1.33	1.44	1.63	1.60	1.68	1.45
											(9.14)
B/M	1.47	1.32	1.19	1.06	1.00	0.92	0.84	0.77	0.68	0.54	-0.93
											(-12.11)
Fixed Inv/Capital	0.08	0.08	0.09	0.10	0.11	0.12	0.14	0.16	0.21	0.35	0.27
											(24.62)
OC Inv/OC	0.31	0.28	0.29	0.31	0.32	0.36	0.41	0.45	0.56	1.45	1.14
											(1.96)
Hiring Rate	-0.08	-0.02	0.01	0.03	0.05	0.07	0.08	0.11	0.17	0.23	0.30
											(16.38)

Table A4: Summary Statistics with Organization Capital

Similar to our benchmark results, TFP is positively and monotonically related to contemporaneous stock returns and negatively related to future returns.

Excess Returns for TFP Sorted Portfolios (%, annualized)

	Contemporaneous Returns (Year *t*)										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Return	-4.02	4.85	7.37	9.99	12.34	14.49	15.54	16.44	20.07	26.34	28.70
t-stat	(-0.92)	(1.32)	(2.22)	(2.92)	(3.51)	(4.18)	(4.40)	(4.45)	(4.94)	(5.87)	(12.60)
Std	25.34	21.52	19.31	19.93	20.50	20.22	20.59	21.53	23.68	26.17	13.28
	Future Returns (Year *t+1*)										
All states, 402 months											
	Low	2	3	4	5	6	7	8	9	High	High-Low
Return	15.23	15.48	13.34	14.78	12.68	11.80	13.17	11.29	10.60	10.15	-4.90
t-stat	(3.48)	(4.23)	(3.98)	(4.42)	(3.74)	(3.46)	(3.87)	(3.17)	(2.81)	(2.39)	(-2.22)
Std	25.50	21.32	19.56	19.52	19.79	19.87	19.86	20.79	22.01	24.82	12.87

Table A5: Excess Returns with Organization Capital

Finally, the cross sectional Fama-MacBeth regression produce a negative and statistically significant average slope. The magnitude of the effect, -5.24, is similar to our previous finding.

Fama-MacBeth Regressions
Dependent Variable: Excess Returns

	Intercept	TFP
1973:7-2007:6	12.56	-5.24
	(3.39)	(-3.07)
1973:7-1990:6	11.10	-5.16
	(1.95)	(-1.89)
1990:7-2007:6	14.02	-5.33
	(2.97)	(-2.57)

Fama-MacBeth Regressions with OC

All other findings with organizational capital are very similar to our benchmark results.